Combining physics models and Gaussian processes for traffic prediction

A. Würth[†,1], M. Binois[§,1], P. Goatin[§,1]

[†] PhD student (presenting author). [§] PhD supervisor

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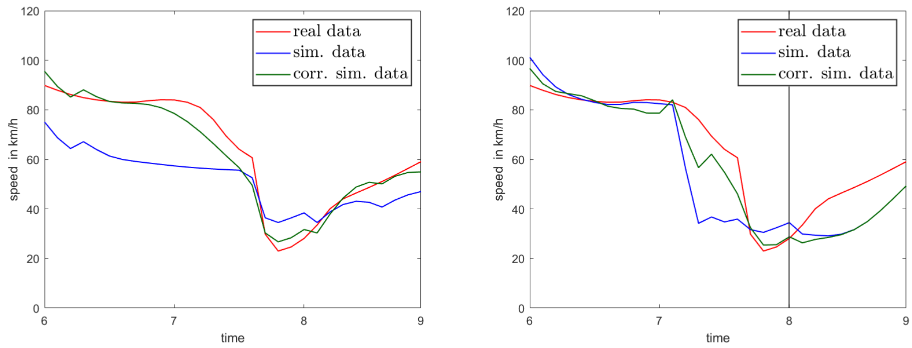
[1] *Université Côte d'Azur, Inria, CNRS, LJAD*, Sophia Antipolis, France
{alexandra.wuerth, mickael.binois, paola.goatin}@inria.fr

Abstract

We propose a Bayesian framework for parameter identification and traffic state reconstruction by macroscopic traffic flow models. Due to limited access to both trajectory and average loop detector data, we perform our analysis on synthetic traffic data generated by numerical simulations. We are interested in the relative travel time error showing that the usage of the traffic flow model leads to reasonable prediction accuracy.

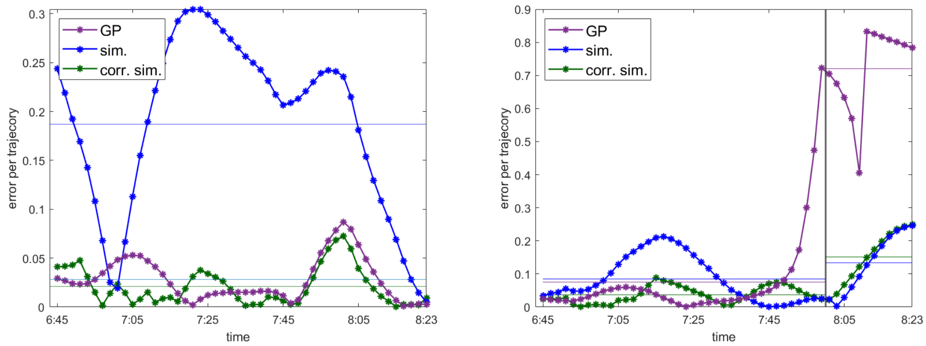
Macroscopic traffic flow models, consisting in hyperbolic partial differential equations based on the mass conservation principle, describe the spatio-temporal evolution of traffic aggregate quantities such as density and mean velocity on road networks. The models are based on a speed function including unknown parameters. Since they involve few parameters and they are computationally less expensive, they are often a preferred choice over other models (such as microscopic ones). Classically, macroscopic traffic models are calibrated by fitting the so-called fundamental diagram i.e., the density-flow or density-speed mapping described by the model flux function (see e.g. [1]). However, data noise and congested traffic situations make the parameter identification process difficult to deal with. Thus, in this work, we consider two different calibration approaches applied to first order models, consisting in the sole mass conservation equation, and second order ones, including a second equation accounting for speed evolution. One approach consists in minimizing the Ł2-error between the simulation output and the (synthetic) data. The other one was proposed in [4] and follows a Bayesian approach which allows us to evaluate the parameter probability distribution given the observed data. Moreover, following Kennedy-O'Hagan [2], we introduce a bias term to better account for possible discrepancies between the mathematical models and reality; this bias term is modeled by a Gaussian process (GP).

Once the calibration parameters are obtained, our analysis distinguishes between travel time estimation and prediction where the former is related to already realized traffic scenarios [3]. For the second one, we apply again a GP to predict future traffic conditions at boundary loop detector locations and sparse time points. These serve as initial data to simulate the traffic conditions at a finer scale, which enables us to do travel time prediction. Finally, we compare the travel times between the ground truth and (by the bias corrected) simulated data observing that the usage of the physics model on top of the GP improves the prediction accuracy.



(a) traffic estimation (b) traffic prediction

Figure 1: Illustration of speed profiles between 6 and 9am at a fixed loop detector position for different data types: real data, sim. (simulated) data and corr. sim. (bias corrected simulated) data. The traffic prediction refers to the time window between 8 and 9am.



(a) traffic estimation (b) traffic prediction

Figure 2: Comparison of the travel time error (for 50 trajectories starting at 6:45am) between 3 different approaches: GP (without physics knowledge), sim. (simulation), corr. sim. (bias corrected simulation).

Short biography (PhD student)

Alexandra Würth is a PhD student, supervised by P. Goatin and M. Binois, in the ACUMES project team at Inria. Her subject, “AI for road traffic modeling and management“, aims to analyze information derived from traffic data using different statistical methods and exploiting them within deterministic PDE models. Alexandra received her M.Sc. at the University of Mannheim in Business Mathematics with focus on numerical methods for hyperbolic conservation laws.

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